

Compositional and lexical semantics

- Compositional semantics: the construction of meaning (generally expressed as logic) based on syntax.

This lecture:

- Semantics with FS grammars

- Lexical semantics: the meaning of individual words.

This lecture:

- lexical semantic relations and WordNet
- one technique for word sense disambiguation

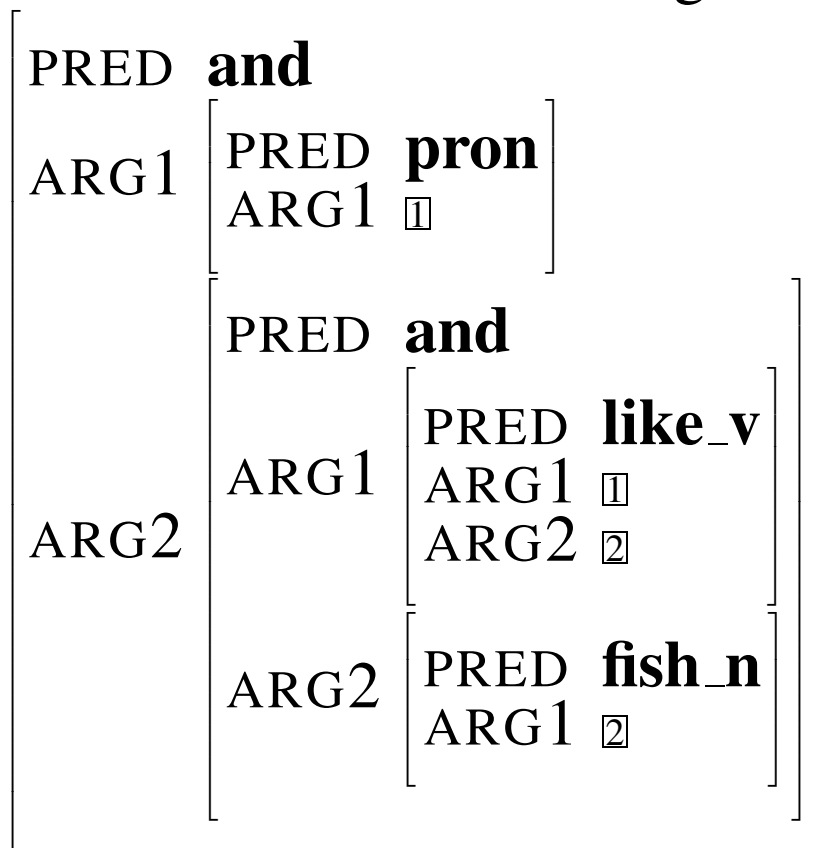
Simple compositional semantics in feature structures

- Semantics is built up along with syntax
- Subcategorization ‘slot’ filling instantiates syntax
- Formally equivalent to logical representations (below: predicate calculus with no quantifiers)
- Alternative FS encodings possible

Objective: obtain the following semantics for *they like fish*:

$\text{pron}(x) \wedge (\text{like_v}(x, y) \wedge \text{fish_n}(y))$

Feature structure encoding:



Noun entry

fish	HEAD	[CAT noun AGR]
	COMP	filled
	SPR	filled
	SEM	[INDEX \mathbb{I} PRED fish_n ARG1 \mathbb{I}]

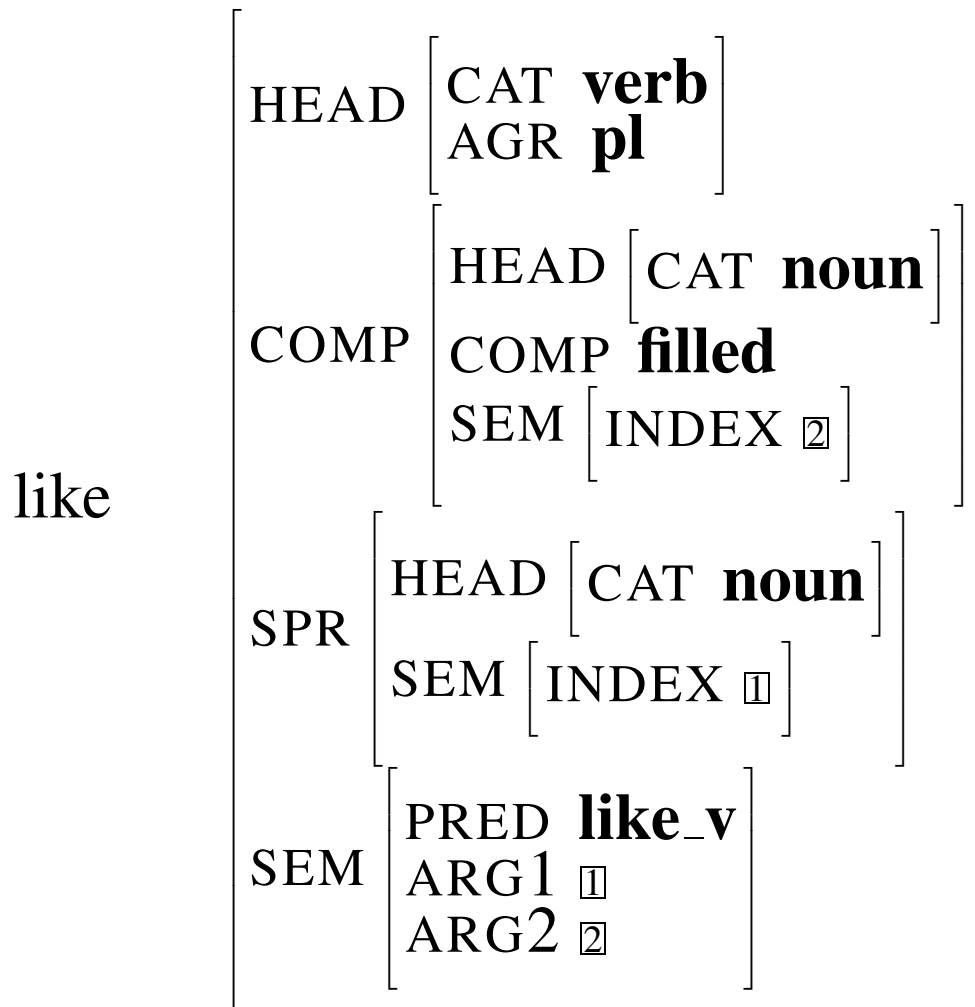
- Corresponds to $\text{fish}(x)$ where the INDEX points to the characteristic variable of the noun (that is x).

The INDEX is unambiguous here, but

e.g., $\text{picture}(x, y) \wedge \text{sheep}(y)$

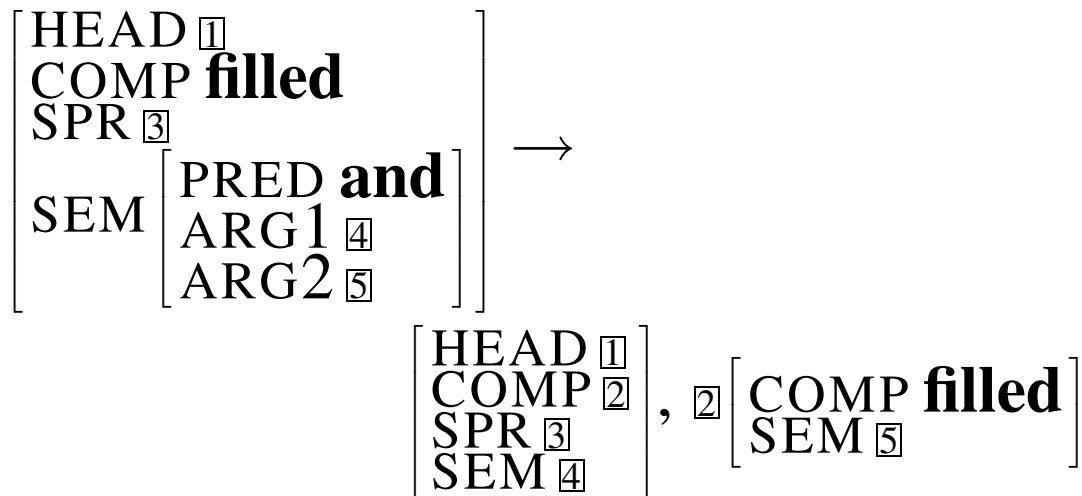
picture of sheep

Verb entry



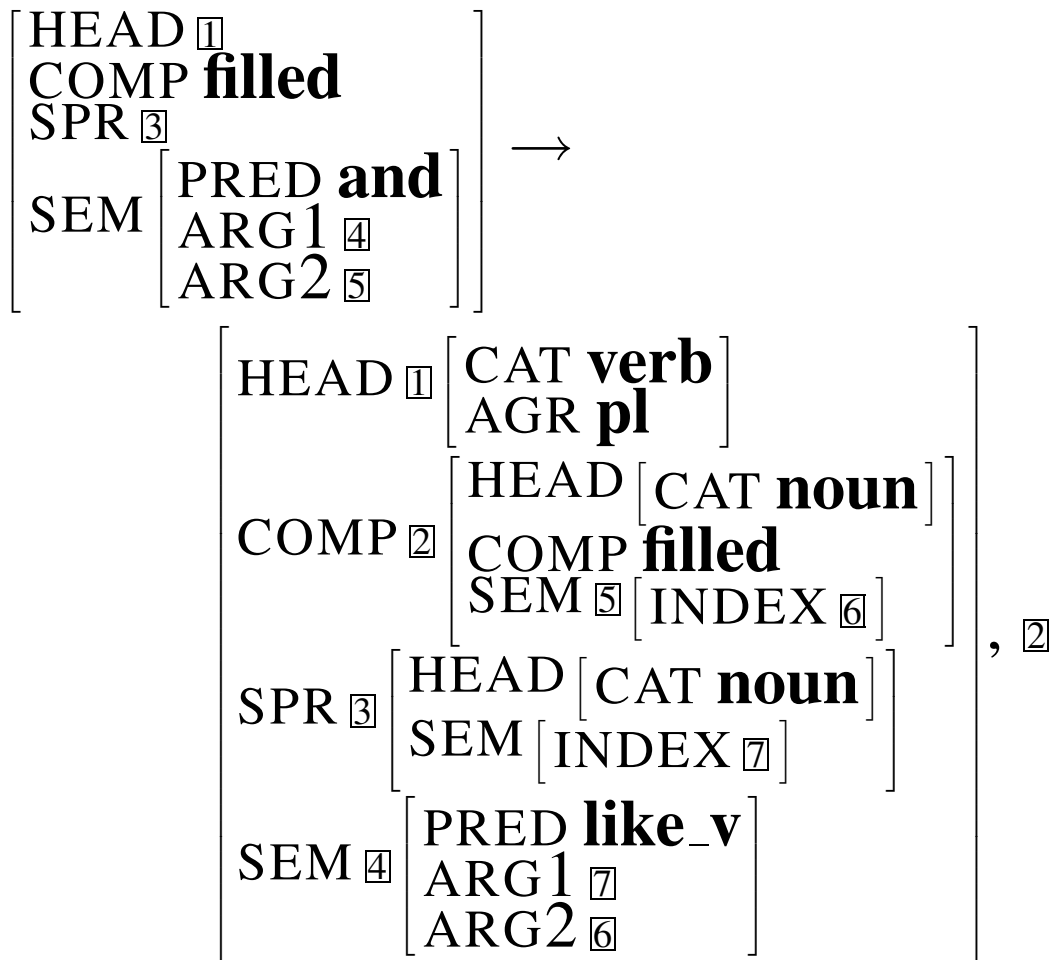
- Linking syntax and semantics: ARG1 linked to the SPR's index; ARG2 linked to the COMP index.

COMP filling rule

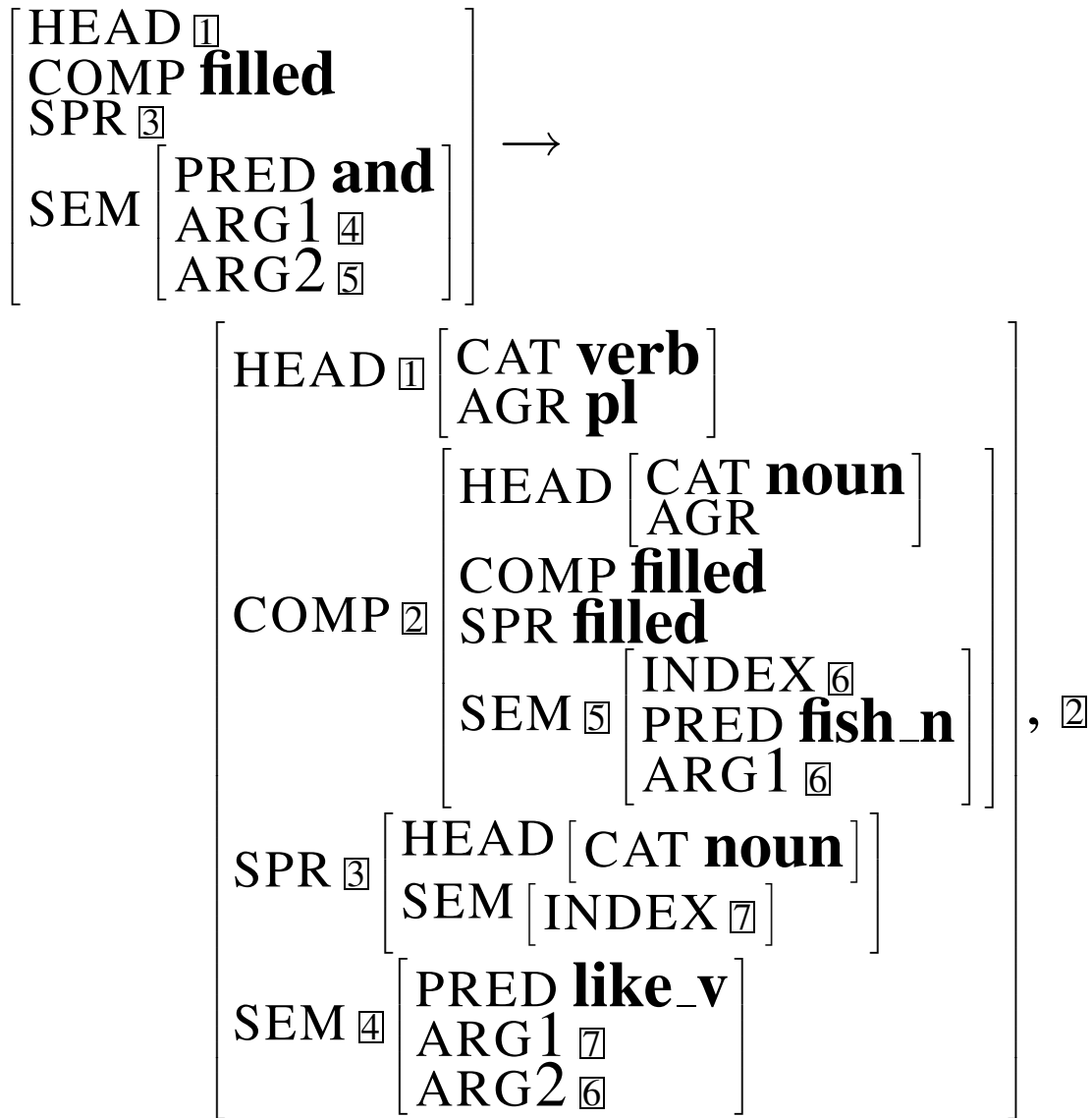


- As last time: object of the verb (DTR2) ‘fills’ the COMP slot
- New: semantics on the mother is the ‘and’ of the semantics of the dtrs

Apply to *like*



Apply to *like fish*



$\text{like_v}(x, y) \wedge \text{fish_n}(y)$

Logic in semantic representation

- Meaning representation for a sentence is called the *logical form*
- Standard approach to composition in theoretical linguistics is lambda calculus, building FOPC or higher order representation
- Representation above is impoverished but can build FOPC in FSs
- Theorem proving
- Generation: starting point is logical form, not string.

Meaning postulates

- e.g.,

$$\forall x[\text{bachelor}'(x) \rightarrow \text{man}'(x) \wedge \text{unmarried}'(x)]$$

- usable with compositional semantics and theorem provers
- e.g. from ‘Kim is a bachelor’, we can construct the LF

$$\text{bachelor}'(\text{Kim})$$

and then deduce

$$\text{unmarried}'(\text{Kim})$$

- OK for narrow domains, but ‘classical’ lexical semantic relations are more generally useful

Lexical semantic relations

Hyponymy: IS-A:

- (a sense of) *dog* is a *hyponym* of (a sense of) *animal*
- *animal* is a *hypernym* of *dog*
- hyponymy relationships form a *taxonomy*
- works best for concrete nouns

Meronymy: PART-OF e.g., *arm* is a *meronym* of *body*, *steering wheel* is a meronym of *car*
(piece vs part)

Synonymy e.g., *aubergine/eggplant*

Antonymy e.g., *big/little*

WordNet

- large scale, open source resource for English
- hand-constructed
- wordnets being built for other languages
- organized into *synsets*: synonym sets (near-synonyms)

Overview of adj red:

1. (43) red, reddish, ruddy, blood-red, carmine, cerise, cherry, cherry-red, crimson, ruby, ruby-red, scarlet -- (having any of numerous bright or strong colors reminiscent of the color of blood or cherries or tomatoes or rubies)

2. (8) red, reddish -- ((used of hair or fur) of a reddish brown color; "red deer"; reddish hair")

Hyponymy in WordNet

Sense 6

big cat, cat

- => leopard, Panthera pardus
 - => leopardess
 - => panther
- => snow leopard, ounce, Panthera uncia
- => jaguar, panther, Panthera onca,
 - Felis onca
- => lion, king of beasts, Panthera leo
 - => lioness
 - => lionet
- => tiger, Panthera tigris
 - => Bengal tiger
 - => tigress
- => liger
- => tiglon, tigon
- => cheetah, chetah, Acinonyx jubatus
- => saber-toothed tiger, sabertooth
 - => Smiledon californicus
 - => false saber-toothed tiger

Some uses of lexical semantics

- Semantic classification: e.g., for selectional restrictions (e.g., the object of *eat* has to be something edible) and for named entity recognition
- Shallow inference: ‘X murdered Y’ implies ‘X killed Y’ etc
- Back-off to semantic classes in some statistical approaches
- Word-sense disambiguation
- Machine Translation: if you can’t translate a term, substitute a hypernym
- Query expansion: if a search doesn’t return enough results, one option is to replace an over-specific term with a hypernym

Word sense disambiguation

Needed for many applications, problematic for large domains. May depend on:

- frequency: e.g., *diet*: the food sense (or senses) is much more frequent than the parliament sense (Diet of Wurms)
- collocations: e.g. *striped bass* (the fish) vs *bass guitar*: syntactically related or in a window of words (latter sometimes called ‘cooccurrence’). Generally ‘one sense per collocation’.
- selectional restrictions/preferences (e.g., *Kim eats bass*, must refer to fish)

WSD techniques

- supervised learning: cf. POS tagging from lecture 3. But sense-tagged corpora are difficult to construct, algorithms need far more data than POS tagging
- unsupervised learning (see below)
- Machine readable dictionaries (MRDs)
- selectional preferences: don't work very well by themselves, useful in combination with other techniques

WSD by (almost) unsupervised learning

Disambiguating *plant* (factory vs vegetation senses):

1. Find contexts in training corpus:

sense	training example
?	company said that the <i>plant</i> is still operating
?	although thousands of <i>plant</i> and animal species
?	zonal distribution of <i>plant</i> life
?	company manufacturing <i>plant</i> is in Orlando etc

2. Identify some seeds to disambiguate a few uses. e.g., ‘plant life’ for vegetation use (A) ‘manufacturing plant’ for factory use (B):

sense	training example
?	company said that the <i>plant</i> is still operating
?	although thousands of <i>plant</i> and animal species
A	zonal distribution of <i>plant</i> life
B	company manufacturing <i>plant</i> is in Orlando etc

3. Train a *decision list* classifier on the Sense A/Sense B examples.

reliability	criterion	sense
8.10	<i>plant</i> life	A
7.58	manufacturing <i>plant</i>	B
6.27	<i>animal</i> within 10 words of <i>plant</i>	A
	etc	

4. Apply the classifier to the training set and add reliable examples to A and B sets.

sense	training example
?	company said that the <i>plant</i> is still operating
A	although thousands of <i>plant</i> and animal species
A	zonal distribution of <i>plant</i> life
B	company manufacturing <i>plant</i> is in Orlando
	etc

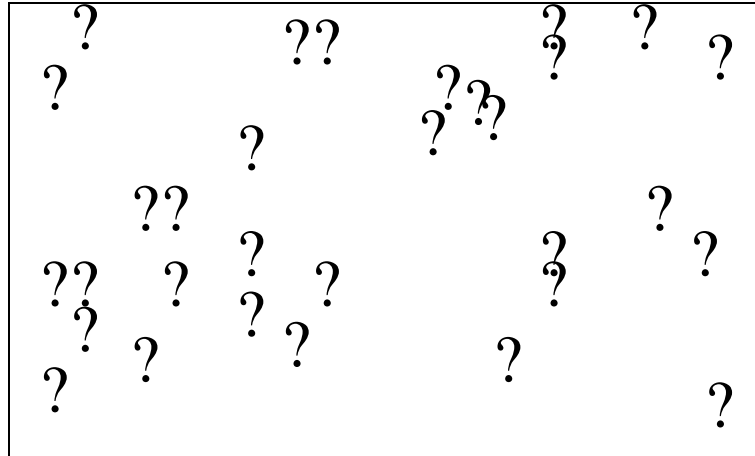
5. Iterate the previous steps 3 and 4 until convergence

6. Apply the classifier to the unseen test data

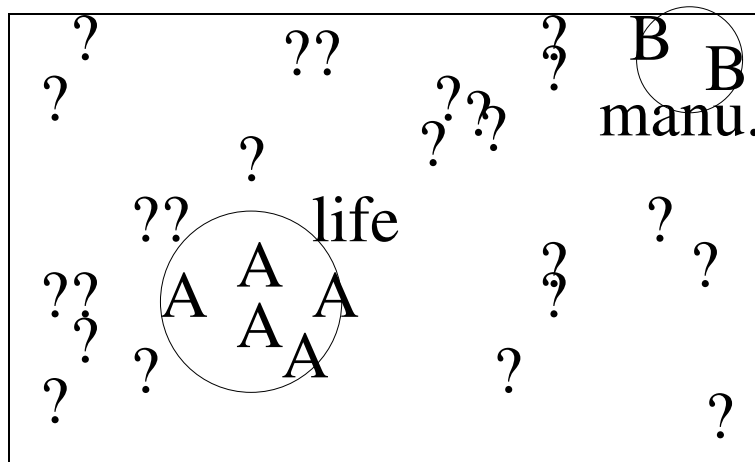
‘one sense per discourse’: can be used as an additional refinement

Yarowsky (1995): schematically

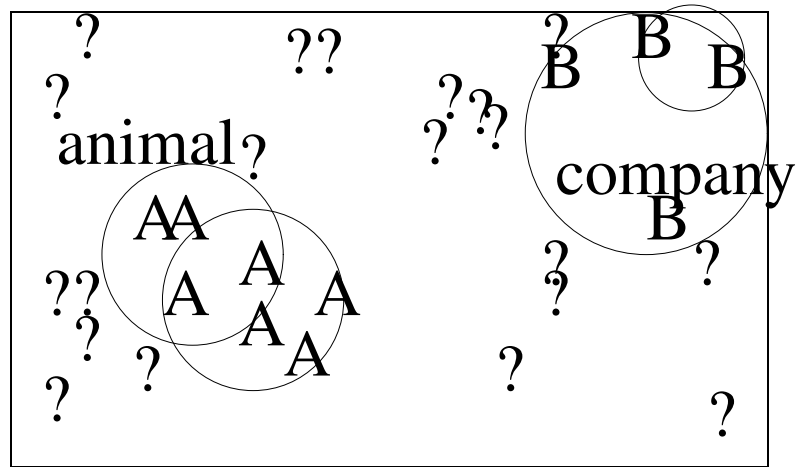
Initial state



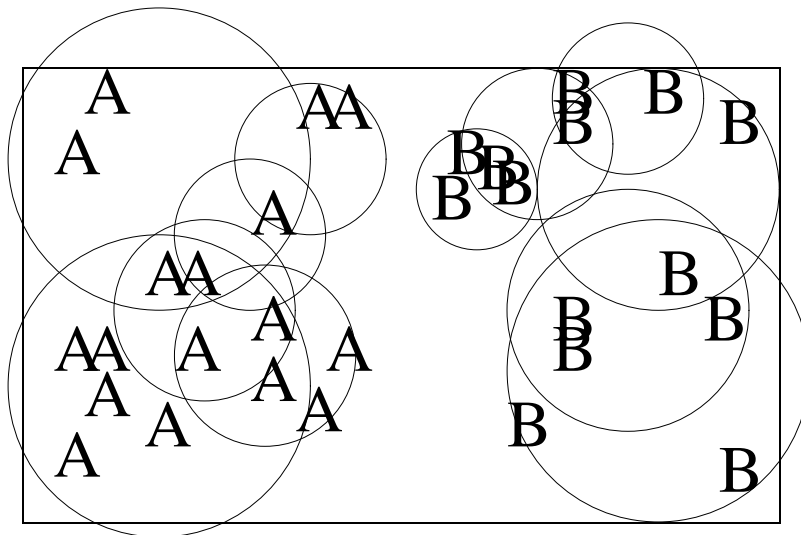
Seeds



Iterating:



Final:



Evaluation of WSD

- SENSEVAL and SENSEVAL-2 competitions
- evaluate against WordNet
- baseline: pick most frequent sense — hard to beat (but don't always know most frequent sense)
- human ceiling varies with words
- MT task: more objective but sometimes doesn't correspond to polysemy in source language